Factors that determine the cost-effectiveness ranking of second-best instruments for environmental regulation

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Abstract This paper develops a conceptual model to analyze how specific factors affect the compliance costs of three suboptimal policy instruments, when compared to the optimal ambient permit system (APS) benchmark. The model considers a non-uniformly mixed pollutant and explicitly incorporates the following factors: number of polluting sources; size, in terms of emissions, of each process; marginal abatement costs for each process; effluent concentrations; the transfer coefficient that relates emissions to environmental quality at the receptor; and the desired environmental quality target. APS is compared to a suboptimal emission permit system (EPS), and two Command and Control (CAC) policies—equal percentage reduction (PER) and a uniform effluent concentration standard (STD). The results show the importance of the different factors and their interactions in determining each policy instrument's cost-effectiveness ranking. Surprisingly, EPS performs well within the usual values of these factors and in specific cases STD and PER also perform similarly to APS.

Keywords Environmental regulation · Policy instrument choice · Cost-effectiveness · Environmental economics · Tradable permits · Command and control

1 Introduction

In theory, both tradable permits and fees have been shown to be cost effective as market based incentives particularly where the market is spatially differentiated (Baumol & Oates, 1971; Montgomery, 1972). Simulation studies have established that cost reductions can be significant using these instruments (O'Ryan, 1996; Tietenberg,

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1985). However, the efficiency gains of an optimal policy[1] are not always substantial. A study for the Los Angeles area, for example, showed that a cost effective policy was only 12% less expensive than command and control (CAC) policies (Hahn & Noll, 1982). Given the potential difficulties of implementing an optimal instrument, the use of second-best instruments[2] with lower costs may be warranted in many specific cases.

This paper develops a formal model to systematically compare the factors that determine the performance of each instrument to show when they are expected to do well, resulting in compliance costs similar to the optimal instrument, and when they do poorly.

Tietenberg (1985) reviewed eight empirical simulations in detail to identify the general factors that determine compliance costs for each policy in the case of non-uniformly distributed pollutants. Four factors are key:

(1) The heterogeneity of firms. This includes both differences in the amount of emissions and the variation in relative marginal costs of abatement among firms;
(2) the number of polluting firms of each type;
(3) the degree of clustering around the receptor that requires the greatest improvements (location), i.e. whether the pollutant is uniformly or non-uniformly distributed; and
(4) the stringency of the ambient standard relative to the level of uncontrolled emissions.

Specifically, the model examines how each of these factors influences the compliance costs[3] of reaching a desired environmental quality standard at a unique receptor location applying alternative policies. Considering a cost-effectiveness approach the model considers the more general case of a non-uniformly distributed pollutant.[4] This is especially relevant for urban and water pollution where many of the pollutants have this characteristic. In developing countries that are now beginning to apply environmental regulations, the issue of how much is to be gained by using market instruments is a usual discussion among policy-makers.

Two previous papers have examined this issue using a cost-effectiveness approach. Newell and Stavins (2003) developed a model that incorporates cost and emission heterogeneity and compares the costs of standards and equal percentage reduction to emission fees or equivalent permits. Heterogeneity is treated as deviations around mean values. Clear results are obtained for a uniformly distributed pollutant, which is very relevant when policy makers need to reach an emission goal. However, their model does not consider the impact of polluting sources considering non-uniformly distributed pollutants, nor the stringency of the required reductions. Russell (1986) developed a formal model to compare the efficiency ranking of two second-best policies for a non-uniformly distributed pollutant. In a simplified setting, using two

[1] "Optimal" and "efficient" will be used in the limited sense of cost-effective in this paper

[2] Transaction and implementation costs are potential problems. See Bohm and Russell (1985) for a discussion of dimensions relevant to the choice of instruments other than cost-effectiveness.

[3] Compliance costs represent total reduction costs. Therefore, the costs include abatement (end-of-pipe) technologies, substitution effects (change in inputs) and output effects.

[4] It is important to notice that the analysis presented is a static and partial equilibrium approach. General equilibrium models have been developed to examine more specific effects such as pre-existing tax distortions. For example see Goulder, Parry, Williams, and Burtraw (1999) or O'Ryan & Miller (2003) for an application in Chile. See also Nichols (1984) and Kolstad (1987) that develop a similar comparison in an optimizing (rather than cost-effectiveness) framework, i.e. considering simultaneously the cost and damage functions.

different point sources, he showed the conditions under which a uniform percentage reduction is more efficient than a uniform charge for a non-uniformly mixed pollutant.

The model developed in this paper, is more general while building on Russell's results. First, it considers explicitly the quantity of emissions (or "size") of the sources. Second the number of polluting firms is included. Third, the model evaluates the importance of the degree of clustering around the receptor location on each policy's cost effectiveness; for example, a comparison of the impact of a few high emitters close to the receptor on the compliance costs as opposed to high emitters distant from the receptor. These differences allow a comparison of policy instruments and their compliance costs under a more general setting than Russell's model where only two sources of the same size are considered. The model also examines a uniform concentration standard as an alternative policy and finally, the effect of the stringency of the policy is incorporated. As is well known, the cost gains from an optimal policy instrument are not significant when low (i.e., close to zero) or very high reductions are required. This latter result, in this case, is because most sources will have to apply the same control technology.

Two questions are addressed using the model. First, how does each of the four, previously identified, factors affect the relative compliance cost of each sub optimal policy instrument? Second, under what combination of the factors is the optimal policy significantly better than other policies, and conversely, when are second best policies a good choice? Using real values for each of the model parameters, the relative compliance costs of three different second best policies are examined and which show interesting regularities that can help the choice of policy instruments.

The following section presents the developed model. In the third section, the model is used to determine the analytic expression for each policies compliance costs. Section 4 examines how each of the four factors determine the cost gains of the optimal policy compared to second-best policies. Section 5 examines the cost-effectiveness ranking of alternative second-best policies for different values of each factor. The final section presents the main conclusions.

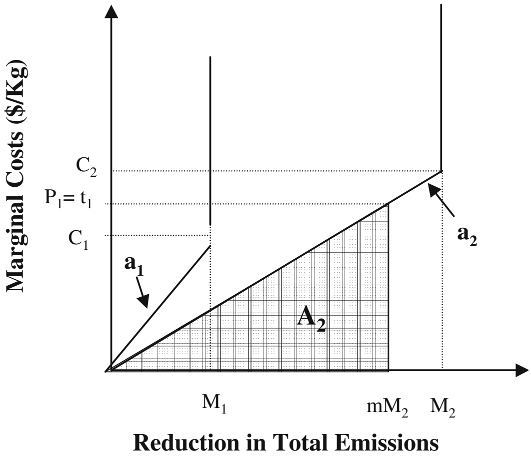
2 The model

This section presents the basic elements of the model developed to establish the compliance costs for different environmental quality targets, with multiple heterogeneous firms located at different distances from a unique or dominant receptor location.[5] The general case of a non-uniformly distributed pollutant is considered.

First, it will be useful to group similar emission sources into categories which will be called processes. Two sources will be considered "identical" processes if they have similar technologies, fuel types, emissions (size), abatement costs, and located near each other. In consequence, many sources may correspond to a single process. For example, in a given city there may be N diesel powered, relatively old, industrial boilers that are medium sized emitters (i.e., that emit one to two tons of a given pollutant), and close to the receptor location. This simplification, which facilitates analysis and

[5] Solving for more than one receptor location requires the use of linear programming techniques. It becomes extremely cumbersome to obtain meaningful stylized conclusions.

Fig. 1 Marginal cost for two processes



policy making, concentrates on the cost differences that actually matter and gloss over smaller differences that are not relevant.[6]

The following are the key parameters of the model:

n: number of different processes;
N_i: number of sources for each process $i, i = 1, \ldots, n$;
a_i: slope of the marginal cost curve for process $i, i = 1, \ldots, n$;
M_i: total emissions or "size" of process $i, i = 1, \ldots, n$;
α_i: transfer coefficient that translates emissions from process $i, i = 1, \ldots, n$, to pollution concentrations at the receptor location.
G_i: Concentration of emissions at the source for process $i, i = 1, \ldots, n$;
Q_0: original environmental quality at the receptor location;
Q^*: the desired environmental quality goal to be reached at the unique receptor.

Any process i is characterized by its marginal cost curve a_i, total emissions M_i—the "size" of the emitting process—its concentration of emissions G_i, and its location relative to the receptor, which is summarized as parameter α_i.

The form of the marginal cost curve is presented for two processes in Fig. 1. Each curve has a constant slope a_i up to M_i. Beyond this point, no further reductions are possible, or, equivalently, marginal costs of reduction are vertical. This formulation captures the fact that in practice the slope of the marginal cost curves are not constant but after a point grow exponentially,[7] and that each process can reduce a maximum of M_i units of emissions because it is applying the best technology available.

From Fig. 1, if a tax is set at a value (t_1) greater than C_1, or the price of permits rises above this value (to P_1), emission reductions by process 1 will reach a maximum of M_1, and emission reductions by process 2 will reach m% of M_2.

[6] This distinction also makes sense from a policymaker's perspective, that needs to decide what type of instrument to focus on in a specific case, without having to model all sources in detail.

[7] An even better approximation to an exponential marginal cost curve can be obtained by assuming that some reductions can be made at zero cost. This has been done, however the resulting formulation is somewhat messy and does not introduce interesting insights.

The transfer coefficient α_i characterizes the impact of each process i on the receptor location[8] Each unit of emissions by process i contributes to ambient concentrations at the receptor location by α_i. The further away from the receptor, the lower the parameter value. Without loss of generality it can be assumed that type 1 processes are closest to the receptor, so that in this case $\alpha_1 = 1$. In the case of a uniformly distributed pollutant, since location does not matter, $\alpha_i = 1$ for all i.

Total initial emissions by any process i are $M_i * N_i$. Consequently, total emissions (TE) by all n processes is:

$$\mathrm{TE} = \sum_{i=1}^{n} M_i * N_i \tag{1}$$

The total costs of abating $m\%$ of emissions by any process i, $TC_i(m)$, will be the area under the marginal abatement cost curve, precisely up to m (area A_2 in Fig. 1). As a result of the simple formulation of the model, $TC_i(m)$ can be determined by the following expression:[9]

$$TC_i(m) = \left(\frac{a_i}{2}\right) * (m * M_i)^2 \tag{2}$$

3 Compliance costs under different policies for *n* processes

In this section, the model is used to determine compliance costs for the optimal ambient based permit system (APS), and three sub optimal policies: equal percentage reduction (PER), uniform emission concentration standard (STD), and a spatially undifferentiated emission permit system (EPS). In terms of cost effectiveness the results for EPS and APS are equivalent to a unique charge and spatially differentiated charges, respectively.

Under APS it is assumed that compliance costs are minimized, i.e., trades among sources are based on their impact on concentrations at the receptor location. As a result the cost per unit of concentration reduced at the receptor location will be equated across processes. An EPS allows that all sources trade on a one-to-one *emission* basis, and as a result, in equilibrium, the marginal abatement costs of each unit of emission (not concentration at the receptor) is equated across processes. This, of course, is not optimal for non-uniformly mixed pollutants. Under PER all sources are required to achieve identical percentage reductions m, and under STD all sources must comply with a maximum concentration standard g measured at the source.

The initial environmental quality Q_0 at the receptor location is given by the following expression:

$$Q_0 = \sum_{i=1}^{n} N_i * M_i * \alpha_i \tag{3}$$

[8] Note that two otherwise identical processes that have different transfer coefficients are treated as different processes.

[9] Simplifying assumptions made are: (i) The abatement cost function is continuous and begins at zero cost; (ii) it is possible to abate 100% of emissions for each process; (iii) marginal costs grow at a constant rate.

As a result of this formulation, the total compliance costs of each policy instrument for reaching a desired environmental quality goal Q^* are presented in the following table, as a function of all known parameters. The derivations are presented in Appendix 1.

As can be seen, the cost expression for PER considers equal percentage reductions (m)[10] by all (n) processes, consequently the total cost of reduction is simply the addition of reduction costs for all processes. In the case of STD, only those l processes emitting a concentration higher than the uniform standard g are required to reduce emissions. As a result of imposing g, sources with different concentration of emissions G_i reduce a different percentage m_i of their emissions. Additionally, the costs depend on the required abatement target Q^*.

Both EPS and APS are market instruments and it can be the case that some processes (q), given a sufficiently high permit price, reduce their emissions to zero,[11] and the rest $(n-q)$ reduce only a fraction of their emissions. If an EPS is used, it will be the case that in equilibrium the price of the permits will be unique, i.e., marginal costs of abatement will be equal across sources. In contrast to EPS, under APS the equilibrium price of each unit of emission depends on the transfer coefficient, and this is reflected in the corresponding equilibrium price and cost equations. If the transfer coefficient is high, the price will be high, reflecting that a source that is close to the receptor must undertake a larger reduction effort than a similar one far from the receptor.

These equations allow the comparison of abatement costs under PER, STD, EPS and APS policies, respectively. A comparison of total compliance costs for different reduction targets is given in Fig. 2 assuming five different processes. The parameters[12] chosen for the example are not intended to be representative but suggest the type of cost relations that can result. These results resemble those obtained from simulation models applied to real cities (see for example Atkinson & Tietenberg, 1982; O'Ryan, 1996).

As expected, APS is the cost-effective policy. All other policies are more expensive and the cost differential can be significant between APS and the other instruments. For example STD is three times more expensive than APS for reaching a 30% reduction target. However, as the required reduction target increases, all policies tend toward the same total cost.

Another interesting feature of the model is that the efficiency ranking of the suboptimal policies depends on the level of required abatement. STD is the most inefficient policy for abatement with low values. However, at approximately 55% required abatement, PER becomes the most inefficient of the policies. Finally, PER actually performs better than EPS at low required abatement levels, i.e., in this range a suboptimal market-based scheme is more expensive than a CAC type policy.

As required abatement increases, there are critical abatement values or switch points above which all policies begin to converge to APS. These results agree with those normally obtained from simulation models. Appendix 2 discusses the importance of the stringency of the desired environmental quality goal in more detail.

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10 Where $m = 1 - \frac{Q^*}{Q_0}$

11 This is a simplification, since some sources may not be able to reduce to zero for technical reasons, however this does not affect the results.

12 The figure uses data for five processes. The number of processes form the first to the fifth process are 1500, 1000, 500, 200, 500, respectively, the size (kg/year) of emissions for each process are 70, 90, 150, 200, 800. The marginal costs ($/reduced PM kg) for each process are 500,000; 300,000; 150,000; 100,000; and 25,000. The values of the transfer coefficient are 0.01, 0.5, 0.3, 0.5, and 0.9. Finally, the values of concentrations at the source are 100, 100, 450, 450, and 450, respectively.

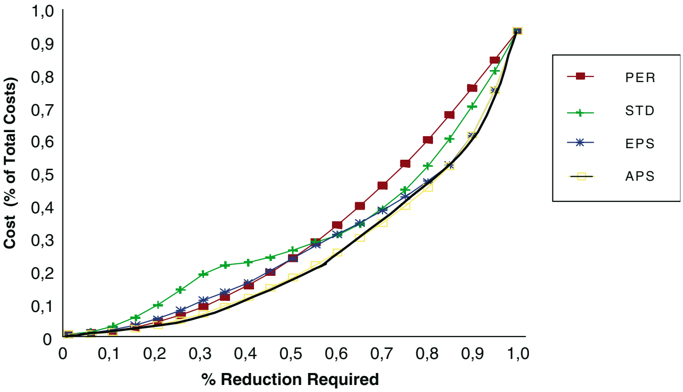

Fig. 2 Cost comparison of different instruments used to improve environmental quality

4 Optimal policy vs. second best policies: importance of each factor in determining the efficiency gains

Each of the factors identified—number of sources per process, heterogeneity of processes i.e. size and abatement costs, location, stringency of the target environmental quality—affect the potential cost reductions of the optimal APS policy compared with the three suboptimal EPS, PER and STD policies. Using the results from Table 1, the compliance costs of the non-optimal policies are compared with those of the optimal policy considering only two processes.[13] This allows simple analytical expressions to be obtained for the corresponding cost ratios.

4.1 Cost ratios to compare the relative efficiency of each policy instrument

It is of interest to examine the influence of each parameter on the relative cost-effectiveness of each second best or suboptimal policy. The following cost ratios will be useful for this analysis:

$$R_0 = \frac{\text{Total Cost under Equal Percentage reduction}}{\text{Total Cost under an Ambient Permit System}} = \frac{\text{PER}}{\text{APS}}$$

$$R_1 = \frac{\text{Total Cost under Equal Concentration Standard}}{\text{Total Cost under an Ambient Permit System}} = \frac{\text{STD}}{\text{APS}}$$

$$R_2 = \frac{\text{Total Cost under Emission Permit System}}{\text{Total Cost under an Ambient Permit System}} = \frac{\text{EPS}}{\text{APS}}$$

If a cost ratio tends to 1, then the second best policy is relatively cost effective, since compliance costs will be similar to APS. Conversely if a cost ratio is very high, the policy is extremely inefficient. Each cost ratio will be estimated using the cost functions from Table 1. To simplify matters, for tractability constant ratios zones are studied. This permits an examination of how the factors interact to determine the magnitude of the cost ratio, independently of the required reduction.

[13] The model allows considering n processes, however only two are needed to examine how each factor affects relative compliance costs. The way the model is set up allows however to consider many emitting sources, because there are N1 sources of process type 1 and N2 sources of process type 2.

Table 1 Compliance costs under each policy of reaching the desired air quality standard Q^*

Policy instrument	Total compliance cost of Reaching Q^* based on known parameters	Additional parameters
APS	$$TC(Q^*) = \frac{1}{2}\sum_{i=1}^{q} M_i^2 * N_i * a_i + \frac{1}{2}\sum_{i=q+1}^{n} \frac{N_i * P_i(Q^*)^2}{a_i} \quad (4)$$ *Note*: To comply with Q^* there are q processes that reduce emissions 100% and $n-q$ processes that each reduce a fraction of their emissions.	$$P_i(Q^*) = \alpha_i \frac{\sum_{i=q+1}^{n} M_i * N_i * \alpha_i - Q^*}{\sum_{i=q+1}^{n} \frac{M_i * N_i * \alpha_i^2}{a_i}}$$ *Note*: $P_i(Q^*)$ is the permit price per unit of emission reduced for each location i.
EPS	$$TC(Q^*) = \frac{1}{2}\sum_{i=1}^{q} M_i^2 * N_i * a_i + \frac{P(Q^*)^2}{2}\sum_{i=q+1}^{n} \frac{N_i}{a_i} \quad (5)$$ *Note*: To comply with Q^* there are q processes that reduce emissions 100% and $n-q$ processes that each reduce a fraction of their emissions.	$$P(Q^*) = \frac{\sum_{i=q+1}^{n} M_i * N_i * \alpha_i - Q^*}{\sum_{i=q+1}^{n} \frac{N_i * \alpha_i}{a_i}}$$ *Note*: $P(Q^*)$ is the unique permit price per unit of emission reduced.
STD	$$TC(Q^*) = \frac{1}{2}\sum_{i=1}^{l} \left(1 - \frac{g(Q)}{G_i}\right)^2 * a_i * M_i^2 * N_i \quad (6)$$ *Note*: It is assumed that under STD only $l <= n$ processes actually reduce emissions given the standard g required to comply with Q^*	$$g(Q^*) = \frac{Q^* - \sum_{i=l+1}^{n} M_i * N_i * \alpha_i}{\sum_{i=1}^{l} \frac{N_i * M_i * \alpha_i}{G_i}}$$
PER	$$TC(Q^*) = \frac{1}{2}\left(1 - \frac{Q^*}{Q_0}\right)^2 \sum_{i=1}^{n} N_i * M_i{}^2 * a_i \quad (7)$$	

Finally, it is convenient to define the following quotients assuming sub index 1 refers to sources close to the receptor:

$M = M_1/M_2$	relative size of both processes;
$a = a_1/a_2$	relative slope of marginal cost curves for each process;
$\alpha = \alpha_1/\alpha_2$	relative transfer coefficients between processes;
$N = N_1/N_2$	relative number of sources between processes;
$G = G_1/G_2$	relative pollutant concentrations at the source, for both process.

These parameters identify the main factors that are key to the gains in policy cost effectiveness: M and a are a measure of the heterogeneity of processes and N, together with α, the degree of clustering around the receptor.

N, M, a can be greater, equal or less than one. For example, if these parameters are all greater than 1, then the process type 1 that is close to the receptor has relatively *many* sources ($N > 1$), is a relatively *large* emitter ($M > 1$), and has a relatively high slope of the marginal cost curve ($a > 1$) or is "*high cost*".

As a result, the following expressions can be obtained for each of the relevant cost ratios:

$$R_0 = \frac{(M^2 * N * a + 1)(\alpha^2 * N + a)}{a(M * N * \alpha + 1)^2} \tag{8}$$

$$R_{1a} = 1 + \frac{a}{N\alpha^2} \qquad (G > 1) \tag{9a}$$

$$R_{1b} = 1 + \frac{N\alpha^2}{a} \qquad (G < 1) \tag{9b}$$

$$R_2 = \frac{(N + a)(\alpha^2 * N + a)}{(N * \alpha + a)^2} \tag{10}$$

It is clear to see that the cost ratios depend on all the parameters: N, M, a, G and α. The behavior of these costs ratios as the parameter values change is explored in the following section.

4.2 Significance of each parameter in the cost effectiveness comparison of policy instruments

Table 2 presents the cost ratios when each of the following parameters tends to extreme values:

For each policy, there are combinations of parameter values that make the cost quotients move to one, indicating that the suboptimal policy is as efficient as APS. For example, PER is as cost effective as APS when three conditions hold: $\alpha = a = M = 1$. In this case all sources are the same so that the cost effective solution requires that all reduce their emissions by exactly the same percentage.

An interesting result from Eq. 8 is that for $Ma = \alpha$, PER is as cost effective, for any value of the other parameters. Multiplying by m on both sides and rewriting this expression we obtain the following relation: $(m * M_1)a_1/\alpha_1 = (m * M_2)a_2/\alpha_2$, that states that marginal reduction costs per unit of concentration at the receptor will be equal; the well known rule for cost effectiveness! Finally, this result is a generalization of Russell's (1986) model that establishes that PER is efficient for $\alpha = a$. However, that model implicitly assumes that $M = 1$ and it is clear that Russell's result will not hold for any other value of M.

The cost ratios can also, in some cases, take both intermediate and very high values. For example, when marginal compliance costs are very different (the quotient a is zero or tends to infinity) PER is very expensive because it imposes similar reduction costs on both processes. The cost effective policy would require that the low cost process make the largest reduction effort.

The influence of each parameter on the relative cost-effectiveness of each second best policy is now briefly examined.

Table 2 Influence of extreme values of parameters in cost effectiveness of second best policies

Parameter	Tends to	PER/APS R_0	STD/APS ($G > 1$) R_{1a}	STD/APS ($G < 1$) R_{1b}	EPS/APS R_2
Location: α	1	$1+\frac{N(Ma-1)^2}{a(MN+1)^2}$	$1+\frac{a}{N}$	$1+\frac{N}{a}$	1
	$+\infty$	$1+\frac{1}{M^2Na}$	1	$+\infty$	$1+\frac{a}{N}$
Number of sources per process: N	0	1	$+\infty$	1	1
	1	$1+\frac{(Ma-\alpha)^2}{a(M\alpha+1)^2}$	$1+\frac{\alpha^2}{a}$	$1+\frac{a}{\alpha^2}$	$1+\frac{a(\alpha-1)^2}{(\alpha+a)^2}$
	$+\infty$	1	1	$+\infty$	1
Amount of emissions: M	0	$1+\frac{\alpha^2N}{a}$	$1+\frac{a}{\alpha^2N}$	$1+\frac{\alpha^2N}{a}$	$\frac{(N+a)(\alpha^2*N+a)}{(N*\alpha+a)^2}$
	1	$1+\frac{N(\alpha-a)^2}{a(\alpha N+1)^2}$	$1+\frac{a}{\alpha^2N}$	$1+\frac{\alpha^2N}{a}$	$\frac{(N+a)(\alpha^2*N+a)}{(N*\alpha+a)^2}$
	$+\infty$	$1+\frac{a}{\alpha^2N}$	$1+\frac{a}{\alpha^2N}$	$1+\frac{\alpha^2N}{a}$	$\frac{(N+a)(\alpha^2*N+a)}{(N*\alpha+a)^2}$
Marginal compliance costs: a	0	$+\infty$	1	$+\infty$	1
	1	$1+\frac{N(\alpha-M)^2}{(\alpha MN+1)^2}$	$1+\frac{1}{N\alpha^2}$	$1+N\alpha^2$	$1+\frac{N(\alpha-1)^2}{(N\alpha+1)^2}$
	$+\infty$	$+\infty$	$+\infty$	1	1

4.3 Relative number of sources N

When N is large, EPS, PER and STD (for $G > 1$)[14] are as effective as APS even if the processes considered are heterogeneous. The reason is that any policy instrument will impose most of the weight of the reduction on the numerous sources close to the receptor. In particular, since in this case $G > 1$, i.e., sources close to the receptor have higher concentration of emissions, so that a low cost solution requires that they bear the brunt of the reduction. This happens when STD is applied. However, when N is low, indicating that there are many type 2 sources (i.e. far from the receptor, with low emission concentration), STD becomes highly inefficient. In this case an efficient solution would require that reductions be undertaken by type 2 sources, without requiring significant reductions from sources type 1. These are few in number and consequently are less relevant for the concentrations at the receptor location.[15] However, STD requires that type 1 sources with high emission concentration reduce first but as they are few, significant reductions from sources type 2 are still needed. There is a high relative cost for this policy option.

4.4 Relative size of sources M

Only the cost quotient R_0 (PER/APS), is influenced by the relative size of the emission sources (M). The size of the process only affects the reductions undertaken as a

[14] We generally assume the case $G > 1$ from now on, to simplify the exposition of results.

[15] High concentrations of emissions (G_i) are not the same as high emissions (M_i). A source can have high concentration of emissions but emit a small amount if it operates few hours per day, or has a low gas flow.

result of PER policy and this percentage only depends on the initial emissions. Given the constant range of the cost ratio being considered here, the cost quotient is not affected by the size of the emitters[16] under APS, EPS and STD as it is independent of the relative size of M.

4.5 Relative marginal cost a

The cost ratios are affected by the relative slope of the marginal cost curves a in different ways. Whenever there is a large difference in relative abatement costs, i.e., for both low and high values of a, PER becomes very expensive and STD is fairly effective for low values of a, but very costly for high values. PERs ineffectiveness at both low and high values of a is because the applied policy moves away from the optimal solution of equating marginal cost of each unit of concentration reduced at the receptor.

However, the explanation of why STD is costly for $G > 1$ are different. Any standard imposed will affect the high concentration of emission (type 1) sources more, requiring that they reduce a higher proportion of their emissions than type 2 sources. If type 1 sources have the lower marginal cost, i.e., a is small, this behavior comes close to an optimal policy, so the cost quotient tends to one. However, if type 2 sources have the lower marginal costs (a is large), the optimal results require that type 2 sources abate more; a result exactly the opposite to the application of a STD policy and consequently this policy becomes very expensive.

4.6 Relative transfer coefficient α

When the relative transfer coefficient tends to 1, EPS is cost-effective (i.e., $R_2 = 1$). This result is expected since $\alpha = 1$ means that the pollutant is uniformly distributed. As α increases, indicating a greater non-uniformity of the pollutant mix, then an equal concentration standard policy (STD) becomes increasingly cost effective for $G > 1$. For large values of the transfer coefficient, the optimal policy requires strong reductions from type 1 process sources, close to the receptor; this is precisely what STD does. However, for $G < 1$, STD is extremely inefficient at high values of α as it requires sources distant to the receptor to reduce emissions unnecessarily.

5 Cost-effectiveness ranking of second-best policies

The model developed can help answer three key questions. Under what combination of the factors is the optimal policy significantly better than the suboptimal policies? When are second best policies comparable with the optimal instrument in terms of effectiveness? What is the cost-effectiveness ranking of the suboptimal policies? As will be seen, there are many plausible cases where suboptimal policies may result in only small cost differences with the optimal policy, making them an interesting policy option.

As in the previous section, for tractability the case of two processes is considered with different plausible combinations of each parameter. Introducing Chilean data

[16] This must not be confused with the fact that larger processes impose higher total emissions as well as larger total costs of reduction. However, the cost quotients compare the relative costs of each policy. In this case APS and all the sub optimal policies are more costly.

in this section provides policy relevant values. The parameter α has been defined as greater or equal to one. Specifically it will be assumed that α can take a low (between 1 and 2) value[17] indicative of a uniformly mixed pollutant, while sources clustered around the receptor location have an intermediate (between 2 and 5) values and those for a strongly non-uniform mixed pollutant have high (between 5 and 50) values.

It is assumed that each of the other parameters (N, M, a) can be greater or less than one, consequently, there are eight possible cases for each value of α (clustering around the receptor).

Case 1: many, small, low cost sources, close to the receptor.
Case 2: many, small, high cost sources, close to the receptor.
Case 3: many, large, low cost sources, close to the receptor.
Case 4: many, large, high cost sources, close to the receptor.
Case 5: few, small, low cost sources, close to the receptor.
Case 6: few, small, high cost source, close to the receptor.
Case 7: few, large, low cost sources, close to the receptor.
Case 8: few, large, high cost sources, close to the receptor.

Based on empirical observations, each of the parameters (N, M, a) is allowed to vary within the following range of plausible values:[18]

The relative number of sources: $N\varepsilon[2, 275]$ for $N > 1$ and $[0.004, 0.5]$ for $N < 1$;

The relative size of sources: $M\varepsilon[1.2, 507]$ for $M > 1$ and $[0.0019, 0.83]$ for $M < 1$;

The relative slopes of the marginal cost curves: $a\varepsilon[1, 12]$ for $a > 1$ and $[0.083, 1]$ for $a < 1$.

Two hundred values were generated randomly for each of the parameters and for each of the three values of α and combined to obtain 200 plausible cases of the cost quotients for each value of α. The results are presented in Table 3. They include the four cost quotients, estimated for each of the above eight cases, considering three possible values of α. The mean value of each quotient is presented together with the standard deviation. The most cost-effective options are shaded in grey.[19]

The results are informative and surprising. Overall, APS is significantly better than the suboptimal policies—defined as a cost quotient greater than two—in only 48% of the randomly generated cases; APS is significantly better than EPS only in 17% of the cases, and in 56% of the cases for STD and PER. The table shows there is a strong case for preferring APS over CAC instruments, although not necessarily over EPS, and not in all cases.

Second best policies are almost as good as APS (grey cells, implying a 10% or less cost differential) in 41% of the cases. As expected, the EPS performs well in 75% of the cases. When sources are clustered around the receptor (low values of α), EPS performs very well because of source-impact homogeneity. However, EPS becomes relatively expensive for high values of α, as in cases 5, 6, 7, and 8. Here the cost-effective result requires significant reductions, mostly for sources close to the

[17] For example in air for Santiago, for every one kilometer the transfer coefficient falls approximately 10%. Sources separated by a distance of 5 km from the receptor would have a transfer coefficient of 2.

[18] These ranges correspond to observed values for Santiago, Chile. The interested reader can see the derivations in the web page http://www.dii.uchile.cl/progea/ or request them from the author.

[19] Assumed as cases in which the cost quotient is less than 1.1.

Table 3 Cost effectiveness ranking of suboptimal policies for the eight possible cases

Transfer coefficient α	Cases (N, M, a)	PER/APS		STD/APS		STD/APS		EPS/APS	
		R0		R_{1a}		R_{1b}		R2	
		Average (SD)		Average (SD)		Average (SD)		Average (SD)	
Low α	1. (Many, small, low)	512.5	483.7	1.00	0.00	2454.43	2330.60	1.00	0.00
	2. (Many, small, High)	4.0	2.8	1.14	0.13	13.69	9.91	1.02	0.02
	3. (Many, big, low)	1.00	0.0	1.00	0.00	1316.53	969.78	1.00	0.00
	4.(Many, Big, High)	1.14	0.13	1.14	0.13	13.69	9.91	1.02	0.02
	5. (Few, small, low)	1.24	0.4	14.76	15.21	1.24	0.43	1.02	0.02
	6. (Few, small, High)	1.01	0.01	124.36	94.27	1.01	0.01	1.00	0.00
	7. (Few, big, low)	1.86	0.61	2.14	0.79	2.29	0.83	1.05	0.04
	8. (Few, Big, High)	106.1	75.6	124.36	94.27	1.01	0.01	1.00	0.00
Intermediate α	1. (Many, small, low)	1170.3	1145.6	1.00	0.00	12399.36	12,367.65	1.00	0.00
	2. (Many, small, High)	9.2	9.4	1.03	0.04	71.92	64.76	1.11	0.08
	3. (Many, big, low)	1.0	0.0	1.00	0.00	7412.92	6894.91	1.00	0.00
	4.(Many, Big, High)	1.03	0.04	1.03	0.04	71.92	64.76	1.11	0.08
	5. (Few, small, low)	2.3	2.5	4.26	4.53	2.32	2.50	1.25	0.19
	6. (Few, small, High)	1.07	0.07	27.48	21.48	1.07	0.07	1.04	0.04
	7. (Few, big, low)	1.18	0.17	1.25	0.22	8.15	5.84	1.38	0.17
	8. (Few, Big, High)	25.4	19.2	27.48	21.48	1.07	0.07	1.04	0.04
High α	1. (Many, small, low)	3675.0	5120.8	1.00	0.00	819,577.88	1,122,670.53	1.00	0.01
	2. (Many, small, High)	130.1	206.1	1.00	0.01	23,358.66	41,181.26	1.08	0.12
	3. (Many, big, low)	1.0	0.0	1.00	0.00	819,577.88	1,122,670.53	1.00	0.01
	4.(Many, Big, High)	1.00	0.01	1.00	0.01	23,358.66	41,181.26	1.08	0.12
	5. (Few, small, low)	87.1	186.6	1.12	0.25	90.83	201.86	5.94	2.85
	6. (Few, small, High)	4.49	11.10	10.68	38.76	4.63	11.91	2.46	2.06
	7. (Few, big, low)	1.35	1.32	1.34	1.70	86.85	197.72	5.59	2.95
	8. (Few, Big, High)	7.3	21.8	10.68	38.76	4.63	11.91	2.46	2.06

receptor. However, providing sub-optimal emission permits that allow trades with the more distant sources on a one-to-one emission basis, results in an over control of these relatively low cost-sources, thus unnecessarily increasing total reduction costs to reach a desired ambient target.

STD and PER perform very well in 29% of the cases. If the regulator has measurements that show information that sources close to the receptor have relatively higher emission concentrations, then, surprisingly, for intermediate and high α, the standard (R_{1a}) performs very well in four of the eight possible cases, with costs very similar to APS! This is because for $G > 1$ and large transfer coefficient values the optimal policy would require strong reductions from type 1 sources, those close to the receptor. This is precisely what equal concentration standards do and is especially true for high values of N (see discussion in previous section). Thus in specific cases EPS and STD are interesting options; EPS where there are low α values and high values of N; and STD where there are high values of α (when $G > 1$). The STD result supports partially the extensive use of standards when the pollutant is non-uniformly mixed. This is adequate from a cost-effectiveness perspective only if the regulator has information that high concentration of emission sources are clustered around the receptor location. However, for the case in which high concentration of emission sources are located far from the receptor ($G < 1$) STD is extremely costly, requiring unnecessary reductions from sources that are far from the receptor.

The standard deviations indicate important results. If they are high (i.e., similar to the mean) then the mean cost quotient obtained does not represent a general case. Consequently, the cost comparison between the two instruments is not robust, being very sensitive to the specific parameters. Conversely, a low standard deviation shows a fairly robust cost quotient for the different parameter values so that the regulator can be fairly sure about the relative compliance costs of different regulatory instruments. For example, in case 7 for an intermediate α, STD/APS ($G > 1$) and PER/APS have high standard deviations. Consequently, for many parameter values, i.e. many possible real life cases, the cost quotient will differ significantly from the mean value. With high standard deviation cases, it is advisable that the regulator use more elaborate simulation models before deciding on the appropriate instrument.

In the cases that the cost quotients are close to one, this quotient is fairly robust to significant changes in each parameter. Sensitivity analysis was carried out, and the range of values was reduced to approximately half and also doubled. Only minor changes in the quotient and dispersion values were observed in these cases. Consequently, for many plausible ranges of parameters, i.e., for many practical applications, the conclusions presented in Table 3 are valid. This is an important result that allows identifying specific cases where policy-makers can be confident that applying second-best instruments does not affect reduction costs significantly and cases where the optimal APS should be preferred.[20]

6 Conclusions

The model developed allows to determine total compliance costs for reaching environmental quality goals under different policy assumptions. It explicitly incorporates

[20] The cost quotients for PER and STD have much more extreme variations than EPS. Using plausible parameter values, both the command and control policies can be 10, 100 or more costly than the optimal policy. Variations in the cost quotients are much less extreme under EPS.

the number of different polluting sources per process; the size, in terms of emissions, of each process; the marginal costs of abatement for each process; and the transfer coefficient that relates emissions at each location to the impact on the receptor's environmental quality. The model also permits assessing the impact on costs of the stringency of the environmental quality goal.

The model permits the analysis of each of the factors that determine the compliance costs of different policies. The basic results show that:

(i) As expected, APS is more efficient than all second-best policies. However, the magnitude of the cost-effectiveness gains depend crucially on the values of specific factors.
(ii) The relative number of emission sources N is key to the cost quotients. When N is large, EPS, PER and STD are as efficient as APS even if the processes are heterogeneous. However, when N is low, STD becomes expensive while PER and EPS remain Cost effective.
(iii) The relative size of emission sources M is only relevant when comparing PER to APS. Equal percentage reduction can be very expensive or fairly cost effective depending on the M value.
(iv) The relative marginal abatement cost curve slope a affects the cost ratios differently. PER becomes very inefficient whenever there is a large difference in relative abatement costs. STD is fairly efficient for low values of a, but very inefficient for high values. EPS performs well for both low and high values, but is inefficient at intermediate values.
(v) Any policy can be optimal but depends on the value of the relative transfer coefficient α. An equal concentration standard policy (STD) becomes increasingly cost effective as α increases, for $G > 1$, but very costly for $G < 1$. EPS is optimal if α is equal to 1. PER is optimal if $\alpha = Ma$.

Thus even though an optimal market-based APS incentive policy is cost effective, there are situations where second best policies can be expected to perform well also.

When plausible combinations of these parameters are considered, the cost quotients show important regularities. First, APS is significantly more cost-effective than other policies in only 48% of cases. In the other cases, the regulator should closely examine the potential use of suboptimal policies. In 75% of the cases , EPS costs are only 10% greater than APS for values of $\alpha < 2$. STD and PER are low-cost in 29% of all possible applicable cases. Moreover, for high α values, STD is cost effective in four of the eight cases ($G > 1$). So, under several possible conditions, when the optimal APS policy has high implementation or transaction costs, EPS and STD are attractive options even considering a non-uniformly distributed pollutant.

In a number of cases when the average cost quotient is considered, some suboptimal policies are fairly efficient. However, a high standard deviation of the quotient shows that there are many combinations where this result does not hold. When there are high dispersions, the regulator should use simulation models to determine whether the use of a suboptimal instrument has costs that may be excessively high under the particular conditions of the problem.

Finally, in the cases that the cost quotients are close to one, this quotient is fairly robust to significant changes in each parameter, indicating that policy-makers can be confident that applying second-best instruments is a low cost option.

The results obtained are useful for examining a range of non-uniformly mixed pollutants policy options. The model demonstrates a systematic way by which to examine how different factors interact to determine costs in specific policy contexts. The simulations inform the policymaker about when a specific instrument can be expected to be cost-effective, and when very inefficient.

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Appendix 1

Derivation of the cost functions for each policy instrument

This appendix presents the derivation of the compliance cost functions for each of the four policy instruments. Note this is just the calculation of the area under the marginal cost curve. Each policy determines different individual reduction requirements that results in different costs. (see Fig. 1)

A.1 Equal percentage reduction (PER)

Under this policy all sources are required to achieve identical percentage reductions m. As a result from Eq. 2, the total cost of reduction is given by:

$$TC = \frac{m^2}{2}\sum_{i=1}^{n} a_i * M_i^2 * N_i \tag{11}$$

However, m is related to the desired environmental quality Q^* by the following relation:

$$Q^* = (1-m) * Q_0 \tag{12}$$

as a result:

$$m = 1 - \frac{Q^*}{Q_0} \tag{13}$$

Substituting (13) in (11) gives the expression for total costs for PER based on known parameters:

$$TC(Q^*) = \frac{1}{2}\left(1 - \frac{Q^*}{Q_0}\right)^2 \sum_{i=1}^{n} N_i {*} M_i{}^2 * a_i \tag{14}$$

A.2 Identical source concentration standard (STD)

Under this policy all sources are required (at least) to meet the same concentration standard g measured at the source. The standard is set such that the desired air quality is measured at the receptor point. To incorporate the concentration standard it is necessary to relate process emissions to emissions concentration level by process. This is done through the following relationship:

$$M_i = G_i * H_i * F_i \tag{15}$$

where M_i is the total emissions from process i (kg/day); G_i is the concentration of the pollutant at the source for process i (kg/m^3); H_i is the hours of operation per day for process i (h/day); F_i is the per hour flow of the gas that contains the pollutant to be controlled, from process i (m^3/h).

Not all sources will reduce the same percentage of their emissions (m_i) as a result of imposing g. It may be the case that, initially, some sources are below the required concentration standard and as a result are not required to reduce emissions at all. Without loss of generality, it can be assumed that there are l sources affected by the standard and $n - l$ not affected. Each of the l processes affected will reduce emissions by m_i, and the others zero. Moreover, after applying the standard, total emissions must reach the desired air quality goal. Final air quality is given by the following relation:

$$Q^* = \sum_{i=1}^{l} N_i * M_i * \alpha_i * (1 - m_i) + \sum_{i=l+1}^{n} N_i * M_i * \alpha_i \tag{16}$$

The first term in the right hand side is the weighted emissions of l sources that reduce for a given standard; the second term is the weighted emissions of the $n - l$ sources that do not reduce. The weight in each case is the transfer coefficient that relates total emissions ($N_i M_i(1 - m_i)$ and $M_i N_i$) at location i with ambient concentrations at the receptor location.

Also, the resulting concentration at the source for each process $(1 - m_i) * G_i$ must equal the allowed standard g, i.e.:

$$m_i = 1 - \frac{g}{G_i} \quad i = l + 1, \ldots, n \tag{17}$$

Substituting (17) into (16), and after some manipulation, gives the following expression for g based on known parameters:

$$g = \frac{Q^* - \sum_{i=l+1}^{n} N_i * M_i * \alpha_i}{\sum_{i=1}^{l} \frac{N_i * M_i * \alpha_i}{G_i}} \tag{18}$$

Finally, to determine total abatement costs under STD only those l processes that actually reduce emissions are considered. As a result, from (2).

$$TC(m) = \frac{1}{2} \sum_{i=1}^{l} m_i^2 * a_i * M_i^2 * N_i$$

or, as a function of g and G_i:

$$TC = \frac{1}{2} \sum \left(1 - \frac{g}{G_i}\right)^2 * a_i * M_i{}^2 * N_i \tag{19}$$

A.3 Emission permit system (EPS)

If an EPS is used, in equilibrium the price of the permits will be unique, i.e., marginal costs of abatement will be equal across sources. For non-uniformly mixed pollutants this is not a cost-effective policy.

Two types of processes can be distinguished: those that at the unique permit price P reduce 100% of their emissions, and those that only reduce a fraction. Figure 1 illustrates this situation for two processes. At price P processes of type 1 abate 100% of their emissions. Assuming there are N_1 sources of this type, total abatement is $N_1\ M_1$.

of Type 2 abate processes m_2. Note that m_2 is equivalent to P/M_2a_2. As a result, the total amount abated by the N_2 type 2 sources at price $P > 0$ s $N_2 * (P/M_2a_2)$.

Generally, it can be assumed that the first q processes will reduce 100% and the other $n - q$ will reduce a fraction m_i of their total emissions. As a result, final environmental quality will be the result of emissions from the $n - q$ sources that emit:

$$Q^* = \sum_{i=q+1}^{n} N_i * M_i * \alpha_i * (1 - m_i) \tag{20}$$

$P(Q^*)$ can be obtained from Eq. (20) and the fact that m_i is equivalent to P/M_ia_i as:

$$P(Q^*) = \frac{\sum_{i=q+1}^{n} N_i * M_i * \alpha_i - Q^*}{\sum_{i=q+1}^{n} \frac{N_i * \alpha_i}{a_i}} \tag{21}$$

And, finally, total costs under EPS are given by

$$TC(Q^*) = \frac{1}{2}\sum_{i=1}^{q} N_i * M_i{}^2 * a_i + \frac{p^2}{2}\sum_{i=q+1}^{n} \frac{N_i}{a_i} \tag{22}$$

In this case q, the number of processes that reduce all emissions depends on the specific parameters of the problem.

A.4 Ambient permit system (APS)

If an APS is used, compliance costs will be minimized, i.e. the result will be cost-effective. In equilibrium, the per unit concentration cost reduced at the receptor $\gamma(Q^*)$ is equated across processes, i.e.:

$$\frac{MC_1(Q^*)}{\alpha_i} = \frac{MC_2(Q^*)}{\alpha_2} = \cdots = \frac{MC_n(Q^*)}{\alpha_n} = \gamma(Q^*) \tag{23}$$

The equilibrium price for an emission unit reduced by any process i is $P_i = MC$. From (m) $P_i = \alpha_i * \gamma$, i.e., the equilibrium price of each unit of emission depends on the transfer coefficient. If the transfer coefficient is high, the price will be high, indicating that a source that is close to the receptor must undertake a larger reduction effort than a distant source.

As in the case for emission permits, two process types are distinguished: q processes that at the equilibrium reduce their emissions by one hundred percent, and $n - q$ processes that only reduce a fraction m_i. The desired environmental quality that results from the $n - q$ emitting processes is:

$$Q^* = \sum_{i=q+1}^{n} N_i * \alpha_i * \left(M_i - \frac{P_i}{a_i}\right) \tag{24}$$

From Eqs. 24 and 23 the equilibrium price for each unit of concentration at the receptor for a given $Q^*, \gamma(Q^*)$, is obtained:

$$\gamma(Q^*) = \frac{\sum_{i=q+1}^{n} N_i * M_i * \alpha_i - Q^*}{\sum_{i=q+1}^{n} \frac{N_i * \alpha_i{}^2}{a_i}} \tag{25}$$

From which $P_i = \alpha_i * \gamma$ can be obtained based on known parameters.

Finally total costs are given by

$$TC(Q^*) = \frac{1}{2}\sum_{i=1}^{q} N_i * M_i{}^2 * a_i + \frac{1}{2}\sum_{i=q+1}^{n} \frac{N_i * P_i{}^2}{a_i} \tag{26}$$

Appendix 2

Importance of the level of required abatement

Cost ratios are constant for all policies in an initial range. For EPS and APS this corresponds to a required abatement set low enough that neither of the two processes has to reduce it emissions by 100%. For STD, the requirement is that only high concentration processes need to abate. The constant ratio in this range is based on the assumption of constant slopes for the marginal abatement cost curves.

However, as the level of required abatement increases, all curves have a critical or switch point (denoted r^*) above which the cost ratio is no longer constant. This switch point can be determined for each cost ratio curve. For example, a switch point occurs for PER vs. APS when, under APS, one of the sources reaches an abatement level of 100%.[21] In this case:

$$r^* = \frac{\left(\alpha * M * N + \frac{a^*}{\alpha}\right)}{(\alpha * M * N + 1)}$$

Clearly r^* depends on all the parameters in the model. For large values of α the switch point tends to one and the constant range of the cost ratio is large. Thus the conclusions of the previous section hold for a broad number of abatement values. However, if type 1 sources are low cost (a is small), few in number (N is small), then r^* is close to zero, and the previous conclusions are limited to low abatement values.

In this example, beyond r^* the cost ratio R_0 depends on the desired air quality Q^* and the original air quality Q_0. Defining $q = Q^*/Q_0$, then:

$$R_0 = \frac{(1-q)^2(N * a + 1)}{(N * a + (1 - q(N * a + 1))^2}$$

i.e., as the desired air quality becomes more stringent (Q^* tends to zero), R_0 tends to one, as expected.

The cost ratio is not as straightforward in the case of EPS and STD. In both cases there is more than one switch point, i.e., more than one point at which the cost ratio varies. For example for STD a first switch point is reached when source 2 processes begin abating under an equal standard. Under APS a second point is reached when

[21] The switch point for STD vs. APS in the example is:

$$r^* = \alpha MN(g-1)/(g(\alpha MN + 1))$$

The switch point for EPS vs. APS is:

$$r^* = \alpha MN(a+1)/(a(\alpha MN + 1))$$

source 1 processes reach their abatement limit.[22] The relative concentration of emissions G plays a role in this case by determining where the switch points are located.

Finally, for all policies the cost ratios tend to one after the first switch point, i.e., they tend to behave like APS.[23] This is expected because at high required abatement levels all policies impose the same abatement technologies.

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[22] This second switch point is at

$$r^{**} = (\alpha MN + a/\alpha)/(\alpha MN + 1).$$

[23] However, at high values of required abatement STD may actually perform relatively worse, before beginning to tend towards the cost under APS.